INCLUSION OF ECG AND EEG ANALYSIS IN NEURAL NETWORK MODELS

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Abstract – **Evaluation of biomedical signals is important in the diagnosis of numerous diseases, chiefly in cardiology through the use of electrocardiograms, and to a more limited extent, in neurology through the use of electroencephalograms. While automated techniques exist for both ECG and EEG analysis, it is likely that additional information can be extracted from these signals through the use of new methods. A chaotic method for analysis of signal analysis variability is presented here that identifies the degree of variability in the signal over time. A second focus is to develop higher order decision models that can incorporate these results with other clinical parameters to represent a more comprehensive view of the disease state, using a neural network model.**

***Keywords* – Signal analysis, neural networks, electrocardiogram, electroencephalogram**

I. INTRODUCTION

Signal analysis data alone can contribute important information for diagnosis and tracking of disease. Electrocardiogram (ECG) results have made major contributions to cardiac diagnosis [1]. The electroencephalogram (EEG) is useful in neurological diagnosis, but to a lesser degree [2]. However, improved methods of analysis may produce additional aspects that are useful [3]. In many cases, combination of signal analysis data with other clinical information results in a more comprehensive analysis. The automation of the entire process requires the construction of higher order processing methodology in which signal analysis results can play a major role. Several possible methodologies exist, including knowledge-based approaches, data-based approaches, and hybrid systems. In data-based approaches, neural networks offer a number of advantages for producing a robust and comprehensive model. Variables from many sources and many data types can be input to the network without requirements of independence of variables.

Two models are described. The first is a method for evaluating the variability in a signal using continuous chaotic modeling [4]. The results of the chaotic modeling can be used directly as an indicator of disease. The second method is a neural network model [5] that can be used in two ways: multiple chaotic parameters can be combined, each as an input node to the network, or chaotic parameters can be combined with other clinical information in the input nodes. The methodology is illustrated in applications to both ECG and EEG data.

II. METHODOLOGY

A. Chaotic Analysis of Signals

In previous work, the authors developed a conjectured solution to the logistic equation that demonstrated that viewing seemingly chaotic systems from a continuous rather than a discrete perspective changed the perception of chaos in the system [4]. Using the continuous approach to chaotic modeling, a method for analysis of chaotic systems, in particular time series, was developed. The basis of this method is the second order difference plot. At time n, the value of the time series is a_n. The second-order difference plot is $a_{n+2}-a_{n+1}$ versus $a_{n+1}-a_n$. Fig. 1 shows a second-order difference plot for a patient with congestive heart failure (CHF). While this visual display is quite useful, it does not present a means of developing a more comprehensive model that can incorporate clinical parameters. For this reason, a number of summary measures were developed that can provide a numerical representation of the plot. The major summary device for the second-order difference plot is the Central Tendency Measure (CTM) that shows how closely points are clustered around the center. The plot in Fig. 1 shows concentric circles of radii 0.2, 0.4, 0.6, and 0.8. The CTM calculates the number of points within the circle for the radius specified by the user. Let t = total number of points, and r = radius of central area. Then

$$\mathrm{CTM} = \left[\sum_{i=1}^{t-2} \delta(d_i)\right]/(t-2) \qquad (1)$$

where $\delta(d_i) = 1$ if $[(a_{i+2}-a_{i+1})^2+(a_{i+1}-a_i)^2]^{.5} < r$ and 0 otherwise.

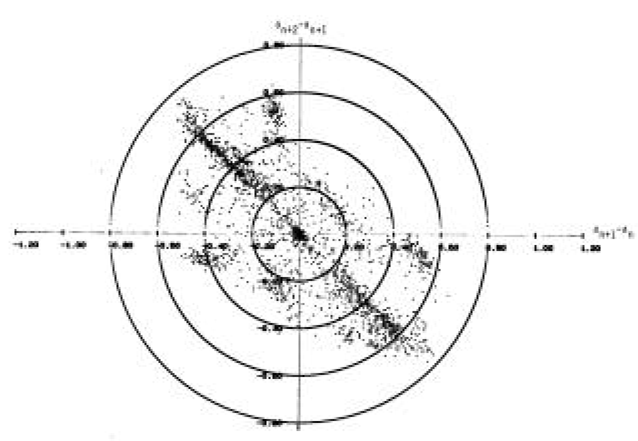

Fig. 1: Second-Order Difference Plot for CHF Patient

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B. Neural Network Model

In previous work by the authors, a non-statistical approach to neural network modeling, Hypernet, was developed based on a potential function approach to supervised learning, which uses the new class of Cohen orthogonal functions as potential functions. This approach has been applied to numerous medical applications over the last decade [5]. The basic neural network structure of Hypernet consists of three layers: the input layer, the hidden layer, and the output layer. Input nodes can be of any type as long as an ordering exists, including binary, categorical, integer, or real. The method generates a decision function of the form

$$D(\mathbf{x}) = \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} w_{ij} x_{ij} \quad (2)$$

where x_i indicates the value of contributing node i, w_i indicates the weight associated with the node, and w_{ij} indicates the weight from the hidden layer to the output layer, which represents the interaction of nodes x_i and x_j.

III. RESULTS

A. Electrocardiogram Analysis

For all ECG studies described in this section, Holter tape data were used. Patients suspected of having cardiac problems are often asked to wear Holter monitors, which are portable devices used make ECG recordings, usually for a 24-hour period. The Holter tapes typically contain in the vicinity of 100,000 points. The method of recording used here consists of the time of each heart beat, a code indicating the status of the recording, two codes indicating possible arrhythmias, and the time between heart beats (R-R intervals). In this analysis, only the last variable, the R-R interval, is used. The rate of change of the heart rate variability is obtained from the second-order differences where a_n represents the R-R interval at time n. An overall CTM measure is then computed. Computation of the CTM for a file containing in excess of 100,000 points takes approximately 30 seconds on the SUN SPARCserver 470 which is used for the CTM calculation as well as Hypernet. Both algorithms can also be run on PC's.

Model Using Chaotic Parameters Alone

Initial studies were made to determine if the CTM gave useful information in differentiating patients with congestive heart failure (CHF) from normal controls. For this purpose, CTM measures were computed using (1) with r = 0.1. Table I shows the results of two studies. Although the difference in means on the second study was statistically significant [6], the ranges on the first study indicate significant overall of CHF and normal subjects [7]. For this reason, expanded studies were undertaken to include additional parameters.

TABLE I
EVALUATION OF CTM MEASURE, CTM(r=0.1)

GROUPS(n)		NORMAL	CHF
CHF (22), Normal (22)	Range	0.623-0.997	0.154-0.987
	Mean	0.90	0.81
CHF (26), Normal (28)	Mean	0.90	0.69 ($p<.01$)

Models Using Chaotic Parameters and Clinical Data

In the next set of studies, two different approaches were taken. Multiple CTM measures were used as input to the neural network to develop a decision function for differentiation between two groups. In addition, clinical parameters were collected that could be combined using the neural network for a more comprehensive model. Table II shows the data collection sheet for the clinical parameters. Table III shows results from four different studies.

In study 1 [8], 32 CHF patients were compared with 32 patients with other types of heart disease. The use of CTM (r=0.1) alone resulted in low sensitivity but high specificity in the identification of CHF patients. Combination of this measure with clinical parameters in a neural network model increased sensitivity and overall accuracy to over 80%.

Study 2 [9] compares 25 CHF patients with 27 normal controls using a neural network model with 4 measures derived solely from the ECG analysis. These included three CTM measures, as well as the total number of R-R intervals in a fixed time period. Sensitivity, specificity, and accuracy were all over 80 %.

TABLE II
CLINICAL DATA COLLECTION

SYMPTOM	TYPE
History of bypass	Y/N
History of MI	Y/N
Presence of symptoms	
Dyspnea	Y/N
Orthopnea	Y/N
PND	Y/N
Duration of symptoms	continuous (minutes)
Physical Findings	
Resting heart rate	continuous
Edema	Y/N
Rales	Y/N
Gallup	Y/N
Mitroregurgitation	Y/N
Functional impairment (NYHA)	(1-3)
LV ejection fractio n	%
Echo	Normal/Abnormal
Exercise time	continuous (minutes)
Holter Data	Y/N
Electrolytes (Na, K, Mg, BUN, Cr)	continuous (for each)
K	continuous
Mg	continuous
BUN	continuous
Cr	continuous
Drugs (Digitalis, Diuretic, ACE Inhibitor, Vasodilators, Anti-arrhythmic)	Y/N (for each)
URI/Viral Syndrome	Y/N

TABLE III
HOLTER TAPE CLASSIFICATION RESULTS

Groups(n)	Variables	Sensitivity	Specificity	Accuracy
C (32), O (20)	CTM Alone (r=0.1)	69%	91%	74%
	CTM with CI*	84%	82%	84%
C (25), N (27)	Combined Holter**	80%	89%	85%
C (52), N (32)	Combined Holter**	83%	88%	85%
CS (22), CD (22)	CTM (r=0.1), CI***	80%	94%	88%

*CI (clinical information): edema, rales, heart rate, BUN
**Holter measures: CTM(r=0.05), CTM(r=0.1), # of RR intervals, lowest value CTM > 0.99
***CI: symptom status (decreased, stable, increased), BUN, orthopnea, dyspnea at rest, heart rate, edema, functional impairment (levels 1-3), PND

C: Congestive Heart Failure
N: Normal Control
O: Other Heart Disease
CS: Congestive Heart Failure, Surviving
CD: Congestive Heart Failure, Deceased

Study 3 repeated study 2 with a larger sample size with slightly improved classification results [10].

Study 4 is a survival analysis that compares 22 surviving CHF patients with 22 deceased CHF patients in an attempt to identify parameters that are predictive of survival [11]. In this model, CTM (r=0.1) and 8 clinical parameters are used in a neural network model.

B. Electroencephalogram Analysis

The traditional approach to EEG analysis, Fourier analysis, provides a quantitative tool to examine signal frequencies and their relative loads. It is almost certain that the conventional Fourier analysis cannot represent the entire spectrum of biological activities. The more comprehensive linear and nonlinear analyses of the EEG signals proposed here not only have practical utility but can also open new windows for studying the significance of the EEG signal in the understanding of the basic neurophysiological functioning of the human cerebral cortex and the visual detection of paroxysmal events such as spikes or sharp waves have been the mainstay of clinical neurological interpretation of EEG recording. EEG analysis is much more complex than ECG analysis in that no repeating pattern exists. There are, however, recognizable wave patterns that appear at indeterminate intervals.

In preliminary studies, the EEG signal was recorded using the Nihon Kohden Corporation Electroencephalograph Model Number EEG-4314B. It has a capacity of up to 21 channels with 2 additional marker channels. A supplemental test system has been designed, implemented, and tested for digitizing EEG data for analysis. A Lab Master analog/digital board form Scientific Solutions has been connected to the electroencephalograph. It is a two-channel single-ended board with 12-bit resolution and a sampling rate of 250/second. Output from the A/D board is sent to a PC computer and is then transferred to the SUN Ultra Enterprise Server 450 for detailed analysis.

To date, EEG recordings have been digitized for 6 patients and 2 normal controls. Data were collected at a rate of 250 samples/second with a periodic 2-second delay for storage requirements. Digital EEG runs lasted approximately 10 minutes and consisted of approximately 75,000 points. Each data point consists of a consecutive number and two channels of output. The output value for each channel is a positive or negative integer indicating the current amplitude. Two channels are selected from the 21 available for this preliminary analysis. The channels selected for recording were T3-T5 and T4-T6. T3 to T6 are based on standard EEG electrode placement. T3-T5 locates over the left temporal area with T4-T6 over the right.

Two methods of analysis were used:

The second order difference plot was generated based on each point in the time series. This analysis is based on amplitude values indicating the level of electrical activity. These results are shown in Table IV.

A peak algorithm was designed to determine the occurrence of significant peaks [12]. Time between peaks was used as a_n, the nth point in the series, to generate the second-order difference plot. This analysis is based on frequency values of the occurrence of the peaks. Results are shown in Table V.

These preliminary studies demonstrate the feasibility of using the CTM for EEG analysis. Current studies are underway to collect additional patient data from three different clinical sources. These data will be randomly divided into a training set and test set. The training set will be used to establish a decision model using the Hypernet neural network. The test set will be used to evaluate the model to determine if these results have clinical significance. Additional testing is underway to determine if preprocessing of using wavelet analysis will contribute to the EEG analysis by permitting the selection of peaks at varying amplitudes.

IV. DISCUSSION

Chaotic analysis of ECG data using the second-order difference plot and the central tendency measure show that the CTM measure is an important factor in the identification of congestive heart failure as a stand-alone indicator. Effectiveness of the classification, however, is significantly enhanced by the use of a neural network model, which allows

TABLE IV
POINT-BY-POINT EEG ANALYSIS, r = 0.1

CATEGORY	CTM
Normal	0.54
Normal	0.71
Alzheimer	0.81
Alzheimer	0.40
Alzheimer	0.67
Alzheimer	0.60
Alzheimer	0.68
Alzheimer	0.58

TABLE V
SAMPLE PEAK ANALYSIS, r = 0.5

CATEGORY	CTM
Normal	0.29
Normal	0.57
Alzheimer	0.52
Alzheimer	0.62
Alzheimer	0.28
Alzheimer	0.44
Alzheimer	0.40
Alzheimer	0.18

either the incorporation of multiple chaotic measures in the same model or using the chaotic measures in conjunction with clinical information. The CTM measure has been shown to be an effective classification parameter in differentiating between CHF and normal controls, between CHF and other heart disease, and in a predictive survival model for CHF patients. In the ECG analysis, the CTM measure is based on the variability of the length of the R-R interval, and is thus based on time parameters alone. In previous work of the authors, the CTM measure was used to analysis hemodynamic data from the hepatic system in an animal model in which the second-order difference plot and subsequently the CTM measure were derived from amplitude information alone, with the amplitude representing the volume of blood flowing at each point in time [13]. Thus the method shows extensibility for the evaluation of different types of signals.

EEG analysis poses particularly difficult problems in the, while events do occur, they do not occur at prescribed intervals. In addition, very little is known about the neurological significance of the overall EEG signal. In spite of this, significant information can be derived from the timing of wave events in the EEG and of the occurrence of these events in multiple EEG channels. The timing of these events can be addressed in a manner similar to the R-R interval analysis in the ECG with results in the time domain. In addition, amplitude information may also be of importance as in the hepatic blood flow analysis. At this point, we are investigating both of these possibilities. Early studies demonstrate that these approaches are indeed feasible. More extensive subject recruitment is underway to determine if this approach will lead to significant clinical findings. In the final model, the chaotic summary measures will be combined with clinical data including evaluation of mental function, family history, and genetic predisposition to form a comprehensive classification model similar to the heart failure model.

V. CONCLUSION

At the basic level, additional techniques for the analysis of biomedical signals are needed. Chaotic approaches have shown promise in providing new insight into these analyses. The CTM approach described here has shown promise in the evaluation of cardiac disorders and hemodynamic studies, and appears to be a promising avenue for EEG analysis. To develop comprehensive classification models, the results of the signal analysis must be incorporated in to higher-level decision models, such as the neural network structure described here. The neural network model provides not only classification results in terms of sensitivity, specificity, and accuracy, but also identifies variables that are important in the decision process along with a weight for each of these variables.

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REFERENCES

[1] B. Babloyantz, P. Maurer, A graphical representation of local correlations in time series - assessment of cardiac dynamics, *Physics Letters A*, **221**:43-55, 1996.

[2] A. Blanco, S. Kochen, O.A. Rosso, P. Salgado, Applying time-frequency analysis to seizure EEG activity, *IEEE EMBS Magazine*, **16(1)**:64-71, 1997.

[3] M.E. Cohen, D.L. Hudson., Chaos and time series analysis, in *Encyclopedia of Electrical & Electronics Engineering*, J.G. Webster, Ed., John Wiley & Sons, pp. 218-226, 1999.

[4] M. E. Cohen, D. L. Hudson, M .F. Anderson, P. C. Deedwania, A conjecture to the solution of the continuous logistic equation, *International J. of Uncertainty, Fuzziness and Knowledge-Based Systems*, **2(4)**:445-461, 1994.

[6] M. E. Cohen, D. L. Hudson, P. C. Deedwania, Application of continuous chaotic modeling to signal analysis, *IEEE EMBS Magazine*, **15(5)**:97-102, 1996.

[7] M.E. Cohen, D.L. Hudson, P.C. Deedwania, Measurement of variability in Holter tape R-R intervals for patients with congestive heart failure, *IEEE EMBS*, 1994.

[8] M.E. Cohen, D.L. Hudson, P.C. Deedwania, P.C., Combining ECG analysis with clinical parameters for diagnosis of heart failure, *IEEE EMBS*, 1997, pp. 50-53.

[9] M.E. Cohen, D.L. Hudson, P.C. Deedwania, Combination of chaotic and neural network modeling for diagnosis of heart failure, *ISCA*, 1997, pp. 254-257.

[10] M.E. Cohen, D.L. Hudson, P.C. Deedwania, M.F. Anderson, Incorporation of image and time series data in a neural network model for medical decision making, 1997, *International Society for Computers and Their Applications*, pp. 101-104.

[11] M.E. Cohen, D.L. Hudson, P.C. Deedwania, Representations of Medical Time Series Using Continuous Chaotic Modeling, *Information Processing and Management of Uncertainty*, 1996, pp. 95-100.

[12] M.E. Cohen, D.L. Hudson, Extension of Chaotic Techniques to Electroencephalogram Analysis, *ISCA Computer Applications in Industry and Engineering*, pp. 82-85, 2000.

[13] M.E. Cohen, D.L. Hudson, M.F. Anderson, C., Vazquez, Blood flow data exhibit chaotic properties, *International Journal of Microcomputer Applications*, **12(3)**, pp. 82-87, 1993.